Computer-Aided Design 36 (2004) 745–757

COMPUTER-AIDED DESIGN

www.elsevier.com/locate/cad

Customizability analysis in design for mass customization

Jianxin Jiao[a,*], Mitchell M. Tseng[b]

[a]School of Mechanical and Production Engineering, Nanyang Technological University, Nanyang Avenue, Singapore, Singapore 639798

[b]Advanced Manufacturing Institute, Hong Kong University of Science and Technology, Hong Kong, China

Received 7 April 2003; received in revised form 7 April 2003; accepted 18 September 2003

Abstract

Product customization has been recognized as an effective means to implement mass customization. This paper focuses on the customizability issue of design, that is, to evaluate the cost effectiveness of a design to be customized in order to meet individual customer needs. Three aspects of customizability are identified, namely, (1) design customizability: the intrinsic nature of product by design, which renders customization to be easy or deficient for either customers or the manufacturer, (2) process customizability: the economic latitude of (production) process variations due to product customization, and (3) the value of customization as perceived by the customers. While design customizability is measured based on the information content metric, the evaluation of process customizability follows the general gist of process capability indices. Conjoint analysis is employed to explore customer preference for multiple product features in terms of utility. Customizability analysis thus exhibits a maximization of customer-perceived value while exploiting the potential of design to be customized by achieving optimal design and process customizability indices.

Keywords: Mass customization; Product design; Customizability; Product and process platforms; Performance measure; Information content; Process capability

1. Introduction

Mass customization [1] aims at best satisfying individual customer needs with near mass product efficiency [2]. The rationality of developing product and process platforms as a means to achieve product variety while maintaining economy of scale has been well recognized in both academia and industry alike [3–6]. The fundamental concern regarding product and process platforms manifests itself through the fact that the company must optimize external variety versus internal complexity resulting from product differentiation [7]. It thus becomes imperative to assess the added value of customization with respect to the impact of customization on the loss of scale economy in design and production. This paper focuses on such a customizability issue. Specifically dealt with is the issue of measuring customizability inherent in the product and process platforms with economic consideration. The goal is to present design and process engineers with insights into product customization and its produceability.

* Corresponding author. Tel.: +65-6790-4143; fax: +65-6791-1859. *E-mail address:* jiao@pmail.ntu.edu.sg (J. Jiao).

0010-4485/$ - see front matter © 2004 Elsevier Ltd. All rights reserved.
doi:10.1016/j.cad.2003.09.012

Some researchers have strived to develop design metrics for tradeoff analysis in customization. Martin and Ishii [8,9] develop quantitative tools to determine customer preference for variety and to estimate manufacturing costs of providing variety. Gonzalez-Zugasti et al. [10] propose a quantitative measure of the value of product families to the company and apply it to select the best design from a set of possible alternatives. Simpson et al. [11] employ a market segmentation grid to identify suitable scaling factors based on which a common product platform can be customized to satisfy a range of performance requirements. They characterize the amount of variety within the product family based on the variation of scaling factors. Conner et al. [12] apply robust design principles to address product family tradeoffs using the commonality and performance indices developed by Simpson [13]. Blackenfelt [14] introduces the quality loss function to facilitate the optimization of the degree of variety within a product platform.

Collier establishes the basis of commonality indices for measuring the degree of commonality underlying a product structure in the form of a bill-of-materials (BOM) [15]. Siddique [16] proposes measures of component commonality and connection commonality based on the analysis of the modular structures of automotive underbodies. Jiao and Tseng extend Wacker and Trelevan's [18] individual indices of component commonality and process commonality to coherent single indices and map out managerial implications regarding tradeoffs between component commonality and process commonality [17]. Kota et al. introduce a product line commonality index to assist product family design [19]. McAdams et al. [20,21] study the issue of similarity measure from a functional design perspective. Jiao and Tseng [22] investigate the fundamental concerns of modularity and commonality as well as the relationships in between. Martin and Ishii [23] propose the generational variety and coupling indices to characterize the impact of market requirements on changes of product platforms over time. Ulrich [24] studies the modularity issue in the context of product architectures.

On the empirical side, existing research on examining the cost consequence of customization and how it affects operational performance has been limited and inconclusive. Ho and Tang [25] discuss the modeling and analysis of value and cost tradeoffs from marketing and economics perspectives. Kekre and Srinivasan [26] investigate the market benefits and cost disadvantages of broader product lines. Banker et al. [27] observe that product complexity has a significant impact on the cost of supervision, control and tool maintenance as well as congestion and quality. MacDuffy et al. [28] suggest that the impact of product variety on performance varies, and is generally much less than the conventional manufacturing wisdom predicts. Herrmann and Chincholkar [29] propose a design-for-production method for designers to evaluate product designs by comparing their manufacturing requirements with an available production capacity and an estimated cycle time. Kusiak and He suggest design-for-agility rules to make product designs robust against the changes in production schedules [30].

While decision making about customizability often involves tradeoffs among the marketing, design and production departments, existing approaches seldom tackle all these aspects within a coherent and integrated framework [31]. Given the multidimensional nature of product and process platforms in build/configure-to-order production, it rises in importance to achieve a synergy of customer needs, products and processes throughout customizability analysis [32].

Towards this end, this paper identifies two sources of customizability, namely, design changes and process variations. Accordingly, two indices are developed for measuring design customizability and process customizability, respectively. The rationale behind a customizability index is to measure the cost-effectiveness of a customization feature in terms of the customer-perceived value and the associated flexibility in product and process platforms. The utility theory is applied to model the customer-perceived value of each individual product feature. Conjoint analysis is employed to develop a joint utility of multiple features of a specific customer order. Therefore, customizability analysis can be formulated as either a design evaluation or design optimization problem. The objective is to maximize customer-perceived value of customization while achieving optimal design and process customizability indices.

2. Fundamental issues of customization

Considering the market benefits of customization and the costs of providing variety, it is reasonable to fulfill customization within a company's capabilities in design and production. In practice, this is often achieved by developing product and process platforms [3]. A product platform performs as a base product from which product families can variegate designs to satisfy individual customer requirements. Corresponding to a product platform, production processes can be organized as a process platform in the form of a bill-of-operations (BOO) (e.g. standard routings), thus facilitating build/configure-to-order production for given customer orders [7].

As shown in Fig. 1, the customization process can be illustrated along the entire spectrum of product realization according to the domain framework [33]. A product platform is characterized by a set of design parameters (noted as D), which suppose to meet certain customer needs characterized by a set of functional requirements (noted as F). The corresponding process platform can be characterized by a set of process variables (noted as P). Assume Δ implies certain changes from the platforms in terms of F, D

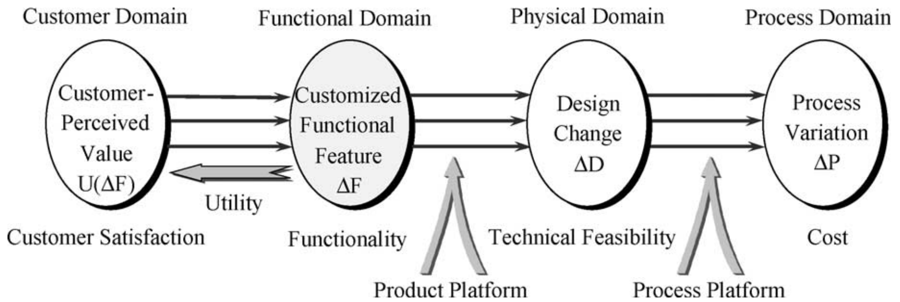

Fig. 1. Multiple views of customization.

or P. A customized product is derived from the platforms by making changes to F, D and P such that the actual product is defined as $F+\Delta F$, $D+\Delta D$, and $P+\Delta P$.

More specifically, customization starts with functionality in the functional domain. A customization requirement, ΔF, is manifested by the customer's choice of customizable functional features and/or their values (options) provided by a product platform (this functional view of product platform is referred to as a product portfolio). The customer-perceived value of each customization requirement indicates customer satisfaction in the customer domain and can be measured as a utility, $U(\Delta F)$.

To deliver the expected ΔF, the product platform (regarded as a base product) needs to be modified to a certain extent (e.g. to change design parameters or configuration), resulting in some design changes, ΔD, in the physical domain. The mapping from ΔF to ΔD exhibits the typical product family design process, where a product variant is derived from the product platform through applying various variety generation methods to the base product [34]. Similarly, in the process domain, the process platform (e.g. a standard routing) needs to be adjusted (e.g. different set-ups), referred to as process variations, ΔP, representing the impact of design changes on production.

As a result, customizability essentially depends on the justification of cost-effectiveness around three pillars: the utility, design changes, and process variations, that is, for all customization requirements,

$$\Delta F \leftarrow \Gamma(U(\Delta F), \Delta D, \Delta P), \quad (1)$$

where ΔF denotes an expected customization in terms of functionality, $U(\Delta F)$ indicates the added value or degree of customer satisfaction of the customization, ΔD characterizes the technical feasibility of fulfilling the customization, and ΔP indicates the costs of fulfilling the customization.

3. Design customizability

Robust design has been widely practiced to make a design insensitive to changes of uncontrollable (noise) factors. The effort aims to bring the mean of performance on target and minimize the deviation of performance [35]. Robustness is achieved by minimizing deviations in performance with respect to *small* changes of noise factors or design parameters [13]. Customization aims to achieve the required deviation of performance by changing design parameters, where the changes may be large or small subjective to the particular design context. Therefore, the major concern of customization is not the robustness but the flexibility of a design to be modified to accommodate variations (deviations) in functional requirements (referred to as expected performance). In other words, design customizability is characterized by the ease (i.e. flexibility) of a change rather than the extent (i.e. robustness) of a change. Indeed, a design easy to change does not consequently deserve good customizability. The contribution of the change to customer satisfaction is another important dimension. A customization difficult in modifying the base design yet producing high customer-perceived value may lend itself to better customizability than a design easy to change whereas less appreciated by the customer.

Suh [33] introduces the information axiom to design evaluation. Flexibility is implied in the measure of information content by associating design performance as achieved performance range (i.e. system range) to the customer expected level of performance as target range (i.e. design range). This paper thus applies the information content measure to assess design customizability while considering both $U(\Delta F)$ and the mapping relationship between ΔF and ΔD.

As shown in Fig. 2, the achieved performance, F_{sr}, of a customized design is described by a probability density function, $p(F_{sr})$, over the system range, $[F_{sr}^{L}, F_{sr}^{U}]$. This is achieved by customizing a base product, i.e. $F_{sr} \leftarrow$ (Base Design $+ \Delta D$). The expected performance, F_{dr}, covers the design range, $[F_{dr}^{L}, F_{dr}^{U}]$. This comes from the customization requirement with respect to the base product, i.e. $F_{dr} \leftarrow$ (Base Spec. $+ \Delta F$).

3.1. Expected performance and preference function

As far as product customization is concerned, a customization requirement is observed as a ranged

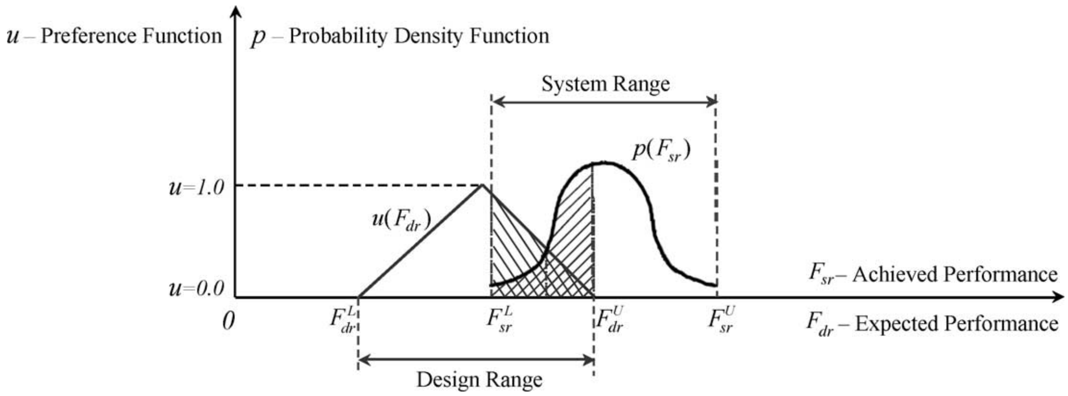

Fig. 2. Preference function and performance distribution.

specification of a particular functional requirement, i.e. $\Delta F \sim [F_{\rm dr}^{\rm L}, F_{\rm dr}^{\rm U}]$, and thus can be interpreted as the expected performance of the customized design, i.e. $F_{\rm dr}$. Over this range, customers usually demonstrate different preferences for specific performance values.

Thurston [36] proposes to construct preference functions based on the utility theory to model customers' preferences over single or multiple product attributes. Chen and Yuan [37] introduce utility theory based preference functions with regard to a ranged set of functional specification. This research applies such a utility theory based preference measure to describe the varying degree of customer preference for different levels of expected performance. A preference function of the expected performance, $u(F_{\rm dr})$, is a function defining the relationship between the degree of preference in terms of utility, u, and a specific level of the expected performance, $\forall F_{\rm dr} \in [F_{\rm dr}^{\rm L}, F_{\rm dr}^{\rm U}]$. The preference function is defined in the range of 0 and 1. Full preference (utility) means a fully acceptable design (performance) and is indicated by $u = 1$. An unacceptable design (performance) corresponds to no preference (utility), i.e. $u = 0$. In general, the preference function may possess various types of forms and is not limited to a triangular function as shown in Fig. 2.

3.2. Achieved performance and performance distribution

Product customization may involve any changes in design parameters or configuration. Most existing research on product family design focuses on the optimal determination of design parameters and/or their values, i.e. 'how' design is to be customized [6]. While the technical details of ΔD are tedious and always domain dependent, this research emphasizes on the *consequence*, rather than the *content*, of ΔD. Such an understanding coincides with the general principle of performance evaluation in design [38,39]. Further taking into account the uncertainty associated with customization solutions, we model product customization as a probabilistic design process and thus describe a customized design (i.e. ΔD) in terms of a probabilistic distribution of the achieved performance of the design, i.e. $p(F_{\rm sr})$. To figure out what types of performance distributions, Monte Carlo simulations or other statistical techniques such as Design of Experiments and Response Surface Models can be employed [40].

3.3. Formulation of design customizability index

Suh's [33] original formulation of information content is derived based on the assumption that the probability density functions of the system and design ranges are all uniform. This may be not sufficient to assess designs with different performance behaviors (e.g. $p(F_{\rm sr})$ in Fig. 2), or the design range assumes different degree of preference (e.g. $u(F_{\rm dr})$ in Fig. 2). As shown by the shaded areas in Fig. 2, the probability of design success can be graphically interpreted as the overlap area of $p(F_{\rm sr})$ and $u(F_{\rm dr})$. If we relax the assumption of uniform distributions, the calculation of the overlap area can not be replaced with the 'common range', $(F_{\rm dr}^{\rm U} - F_{\rm sr}^{\rm L})$, as used in Suh's original formulation. The joint effect of non-uniform probability density functions over the range, $[F_{\rm sr}^{\rm L}, F_{\rm dr}^{\rm U}]$ has to be taken into account. In this regard, this research extends the information content measure to this more general case, as described next.

The information content, I, is measured in terms of the probability of success of a design, $P(F_{\rm sr})$, in meeting the expected performance, $F_{\rm sr}$, as the following:

$$I = -\log_2 P(F_{\rm sr}). \tag{2}$$

Mathematically, the probability of success can be defined as the *expected preference function value* of (achieved) design performance over the range of design solutions, i.e.

$$P(F_{\rm sr}) = E[u(F_{\rm sr})] = \int_{F_{\rm sr}^{\rm L}}^{F_{\rm sr}^{\rm U}} u(F_{\rm sr}) p(F_{\rm sr}) {\rm d}F_{\rm sr}. \tag{3}$$

Theoretically, information content is a cardinal measure, i.e. $I \in [0, \infty)$, which does not give an indication of the difference in evaluation. For comparisons of different criteria on a common basis, it would be more useful to have a relative index that bears absolute boundaries. Therefore, the design customizability index, $\mathrm{CI}^{\rm D}$, can be defined as a modified information content measure, i.e.

$$\mathrm{CI}^{\rm D} = \frac{1}{1 - \log_2 \int_{F_{\rm sr}^{\rm L}}^{F_{\rm sr}^{\rm U}} u(F_{\rm sr}) p(F_{\rm sr}) {\rm d}F_{\rm sr}}. \tag{4}$$

This index is used as a measure to evaluate a customized design in terms of the goodness of its varying performance in successfully satisfying a ranged set of customization requirement. The value of $\mathrm{CI}^{\rm D}$ ranges from 0 to 1, where $\mathrm{CI}^{\rm D} = 0$ corresponds to $I = \infty$, indicating zero degree of customizability (i.e. the worst design), and $\mathrm{CI}^{\rm D} = 1$ is equivalent to $I = 0$, representing the maximum degree of customizability (i.e. the best design). As a relative measure, $\mathrm{CI}^{\rm D}$ represents the degree of a design to be customized cost-effectively compared with the maximum amount possible.

Three different designs that assume different values of $\mathrm{CI}^{\rm D}$ are shown in Fig. 3, where a trapezoid preference function is assumed. In design (a), the preference function

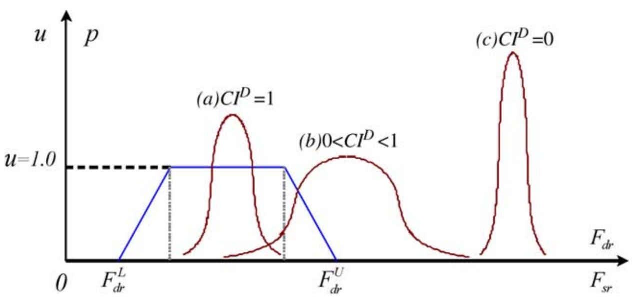

Fig. 3. Implications of design customizability index.

remains 1 over almost the entire system range, then

$$\mathrm{CI}^{\mathrm{D}} = \frac{1}{1 - \log_2 \int_{F_{\mathrm{sr}}^{\mathrm{L}}}^{F_{\mathrm{sr}}^{\mathrm{U}}} p(F_{\mathrm{sr}}) \mathrm{d}F_{\mathrm{sr}}} \approx 1. \tag{5}$$

This is the most desired situation, meaning that the design is easiest to customize. Nevertheless, $\mathrm{CI}^{\mathrm{D}} = 1$ cannot be achieved by designs (b) and (c). It is noteworthy that design (c) yields the poorest flexibility in customization ($\mathrm{CI}^{\mathrm{D}} = 0$) yet the minimal standard deviation, which indicates the least variability (related to robustness).

3.4. Handling multiple customization requirements

In practice, some customization requirements may involve linguistic variables due to their qualitative nature. To deal with this type of intangible performance criteria, fuzzy numbers have been introduced to express imprecise levels related to qualitative variables. In this case, the preference function, $u(F_{\mathrm{dr}})$, keeps the same definition except that the expected performance becomes a fuzzy variable, which is specified as a fuzzy number, i.e. $F_{\mathrm{dr}} \in [F_{\mathrm{dr}}^{\mathrm{L}}, F_{\mathrm{dr}}^{\mathrm{U}}]$ and $0 \le F_{\mathrm{dr}}^{\mathrm{L}} < F_{\mathrm{dr}}^{\mathrm{U}} \le 1$. The achieved performance is also treated as a fuzzy variable and specified as a fuzzy number, i.e. $F_{\mathrm{sr}} \in [F_{\mathrm{sr}}^{\mathrm{L}}, F_{\mathrm{sr}}^{\mathrm{U}}]$ and $0 \le F_{\mathrm{sr}}^{\mathrm{L}} < F_{\mathrm{sr}}^{\mathrm{U}} \le 1$. The performance distribution, $p(F_{\mathrm{sr}})$, is replaced by the membership functions specified for the universe of discourse of fuzzy variable, F_{sr}.

Moreover, in the general case of multiple customization requirements, i.e. $F_{\mathrm{dr}} \sim F_{\mathrm{sr}} \sim \{F_i|_{i=1,\ldots,n}\}$, the probability of success of design becomes a joint probability. When all performance variables are assumed to be achieved independently [33], the joint probability is given by

$$P(F_{\mathrm{sr}}) = \prod_{i=1}^{n} P(F_i). \tag{6}$$

Then the design customizability index for multiple performance variables can be obtained as the following:

$$\mathrm{CI}^{\mathrm{D}} = \frac{1}{1 - \sum_{i=1}^{n} \log_2 \int_{F_i^{\mathrm{L}}}^{F_i^{\mathrm{U}}} u(F_i) p(F_i) \mathrm{d}F_i}, \tag{7}$$

where $F_i \in [F_i^{\mathrm{L}}, F_i^{\mathrm{U}}]$, $\forall i \in [1, n]$. However, such an independence assumption seldom holds true in most design problems. Thus, design customizability evaluation becomes a general multicriteria decision making problem. This issue is discussed in Section 6.

4. Process customizability

4.1. Process platform

The direct consequence of product customization in production is observed as an exponentially increased number of variants [41]. Design changes related to product variety usually result in frequent process variations (referred to as process variety). Similar to the concept of product platforms for dealing with product variety, process platforms should be developed to accommodate process variety. The idea of developing product and process platforms is to achieve mass production efficiency by utilizing reusability underlying product diversity and process variations, in which a set of similar variants share common product and process structures and thus variety can be differentiated within these common structures. This research proposes to develop a process platform based on the generic bill-of-materials-and-operations [7]. Fig. 4 shows the principle of a process platform, in which BOM and BOO data are synchronized into a unified generic structure.

A process platform, Ω, is defined as a triplet as the following:

$$\Omega = (G_{\mathrm{BOM}}, G_{\mathrm{BOO}}, G_{\mathrm{P}}), \tag{8}$$

where G_{BOM}, G_{BOO} and G_{P} stand for a generic BOM, BOO and planning, respectively. A generic BOM (GBOM) represents the product structures of a product platform [42]. It is defined as a tuple as the following:

$$G_{\mathrm{BOM}} = (P, S_{\mathrm{BOM}}), \tag{9}$$

where P and S_{BOM} denote a generic product and a generic goes-into relationship, respectively. As shown in Fig. 4, a generic product may be an end-product (P), a sub-assembly (SA), a component (C), an intermediate part (I), or the raw material (R). The generic goes-into relationship describes

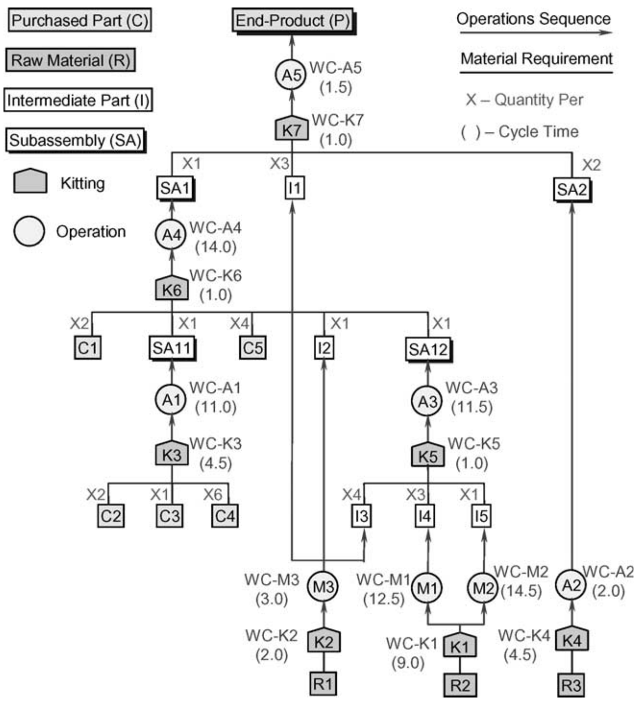

Fig. 4. An illustration of process platform.

the hierarchical structure of an end-product consisting of sub-assemblies, components, intermediate parts, and raw materials. In addition to the parent–child relationships, the S_{BOM} also include such attributes as the quantity-per and cycle times.

Routing information is concerned with how a product is to be produced, that is, the specification of operations sequences to be performed at corresponding work centers along with related resources such as machines, labors, tools, fixtures and setups. A generic BOO (GBOO) can be used to represent the process structures and related production data for producing a given product platform. Fig. 4 also illustrates the GBOO in a form similar to process flow diagrams. The corresponding operations data of a manufactured end product and intermediate parts/sub-assemblies is also shown in Fig. 4. In general, a GBOO is defined as a tuple as the following:

$$G_{\mathrm{BOO}} = (O, S_{\mathrm{BOO}}), \tag{10}$$

where O and S_{BOO} refer to a generic operation and a generic routing, respectively. As shown in Fig. 4, a generic operation may be a machining (M), assembly (A), or kitting (K) process, and thus can be described in terms of its attributes in a 4-tuple, i.e.

$$O \sim \{(P, \mathrm{WC}, \mathrm{RT}, \mathrm{FS})\}, \tag{11}$$

where P, WC, RT, and FS represent the generic product, work center, runtime, and tool/fixture/setup requirements associated with the operation, respectively. The generic routing describes the sequential relationships between all operations involved in a process platform.

Generic planning, G_{P}, is introduced to derive specific process variations in operations routings in order to accommodate diverse product variants related to a generic product (i.e. a product platform). Within a process platform, the variation of an operation results from the differences in product variants to be processed by this operation. The relationships between the GBOM and the GBOO are embodied in the material requirements of production operations. As conceptually described in Fig. 4, the material requirement link between GBOM and GBOO data can be established by introducing a kitting process to each operation and specifying each component material in the GBOM as required by the relevant operation of the GBOO for making its parent product.

To synchronize product and process variety, generic planning employs a generic variety structure [7] for the indirect identification [43] of generic products and operations. While a BOM associates each component material directly with its parent product, generic planning associates a component material with the relevant operation in the GBOO for producing its parent component. For each manufactured end or intermediate product, a single-level BOO structure can be derived by specifying the sequence of operations required for producing that product together with materials and resources (work centers) required for each operation. The multilevel BOO can be composed by linking the single-level BOOs of lower-level intermediate parts through the operations that require them. Through consistent use of variety parameters and their value set embodied in the class–member relationships, the correspondence between generic product structures and routings can be maintained [7]. While a generic product and a generic operation are characterized by variety parameters and their instances, the derivation of specific routings and related process data exhibits the instantiation of the process platform with respect to particular variety parameters and their values.

4.2. Performance indicator of process variations

While the issue of product costing is always implied in design, the majority of costs are actually committed in the production stage. Product design can only be fulfilled through production processes, in which various types of resources are involved and thus become the ingredients of product costs. As shown in Fig. 1, the technical feasibility of a customized design is the major concern in the physical domain, whilst the cost of the customization is reflected in process variations in the process domain. Traditional approaches to product costing is based on the estimation of various cost components such as materials, machine hours, direct labors, administration, and engineering costs. The formidable hindrance of cost estimation lies in its reliance on detailed knowledge of product design and process plans. However, a complete description of the product is not available at the conceptual phase, nor are the relationships between design parameters and their cost figures to be committed in manufacturing in the early design stage.

To circumvent the difficulties in estimating the costs, this research proposes to use cycle times as the performance indicator of process variations. In fact, the cycle time, or lead time, is a very useful performance measure of production [44]. Many factors affect cycle times, such as batch sizes, processing and set-up times, variances on processing and setup times, product mix, routing, etc. Comparing with those manufacturing-oriented performance measures (e.g. high machine utilization), the cycle time suggests itself as a customer-oriented performance measure. Therefore the cycle time is used here as an indirect measure of the costs of process variations to assess customizability in the process domain.

There are many approaches in the field of production planning and control to determine cycle times [45]. Based on standard routings established in a process platform, patterns of cycle time determination can be extracted from historical data and used to extrapolate the cycle time performance for a customized design. The feasibility is embodied by the well-recognized principle of establishing time standards for improving labor efficiency and organizational performance, such as work measurement and time study [46]. In practice, most companies have laid the groundwork for predetermined time standards such as Motion Time Analysis, Work-Factor, Basic Motion Time Study, and Methods of Time Measurement. Jiao and Tseng [47] introduce the systematic procedures to establish relationships between key design parameters and standard times. In addition to these time-estimating relationships (TERs), the best, worst and mean cycle times of a given product platform with respect to the process platform can also be established and employed as benchmarks to compare the cycle time performances of different customized designs. In other words, difference between an estimated cycle time and the baseline indicates the performance of customization in terms of process variation.

4.3. Formulation of process customizability index

The formulation of process customizability index, CI^P, is based on the process capability indices, an approach to quality control in manufacturing. The quality characteristic for the cycle time is of 'the smaller the better' type. The cycle time is of the distinction of most variables that differ as a result of random error and are often well described by the normal distribution [44]. Hence the one-side specification limit indices proposed by Kane [48] can be used, as shown in Fig. 5, namely

$$CI^P = \frac{USL_T - \mu_T}{3\sigma_T}, \tag{12}$$

where USL_T, μ_T, and σ_T are the upper specification limit, the average, and the standard deviation of the cycle time, respectively. Variations in the cycle time are characterized by μ_T and σ_T, reflecting the compound effect of customization on production in terms of process variations (i.e. $\Delta P \sim \{\Delta P_i|_{i=1,\dots,q}\}$).

The USL_T can be determined based on the worst case analysis of a given process platform, where a GBOO is used to accommodates various products customized from the same product platform. In practice, efforts in standard time study can also contribute to the evaluation of USL_T.

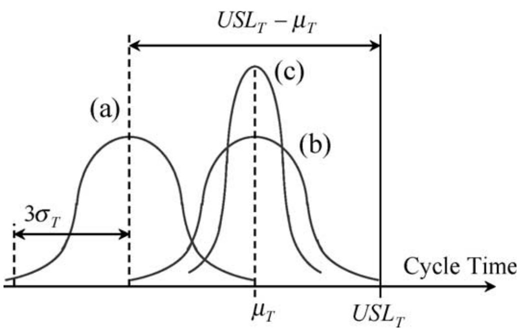

Fig. 5. Process customizability index.

The CI^P is used as a measure to evaluate the extent of process variation, resulting from customization, in terms of cycle time performance. As there is a positive relationship between costs and the cycle time [44,47], this index also gives an indication of how expensive of a customization is to be if implemented in production. Modeling the economic latitude of customization as cycle time performance can alleviate the difficulties in traditional cost estimation which is tedious and less accurate.

The value of CI^P ranges from 0 to 1, where a large value suggests the related production is easy/cheap, and a small value a difficult/expensive one. The CI^P for three different processes of customization are shown in Fig. 5. While σ_T measures the spread of the process in regard to the specification range, μ_T indicates the offset from the target. Processes (a) and (b) posses the same σ_T yet different $\mu_T(\mu_T^{(a)} < \mu_T^{(b)})$ and thus process (a) has better customizability, i.e. $CI^P_{(b)} < CI^P_{(a)} < 1$. Processes (b) and (c) posses the same μ_T yet different $\sigma_T(\sigma_T^{(b)} > \sigma_T^{(c)})$, thus $CI^P_{(b)} < CI^P_{(c)} < 1$, suggesting process (c) is less expensive.

4.4. Managerial implications of process customizability index

According to the conditions of one-side specification limits for a 'smaller the better' type quality characteristic [48], the process yield can be inferred:

$$\%\text{yield} = F_x(\text{USL}). \tag{13}$$

Under normal conditions, the index exhibits a one-to-one relationship with the process yield. The relationship is given by

$$\%\text{yield} = \Phi(3CI^P), \tag{14}$$

where Φ is the cumulative distribution function for a standard normal distribution. As a result, the CI^P directly reflects the process yield because the process yield increases as the CI^P increases. For example, for a 84.134% process yield, $CI^P = 1/3$; and for a 99.865% process yield, $CI^P = 1.0$.

5. Customer perceived value of customization

Du et al. [49] study the construction of utility functions for quantifying the customer-perceived value of customization. Starting from an experiment design of ranges and levels for each customization requirement, test profiles are constructed and presented to the respondents to access customer preferences according to appropriate scales of utility. Then the customer's subjective preference for customization should be quantified as the utility with respect to the overall performance of product features. Based on such a quantitative measure, standard statistical analysis techniques may be used to estimate the utility function. For example, the part-worth and configural models are popularly used preference models.

Customization usually involves multiple requirements, i.e. $\Delta F \sim \{\Delta F_i|_{i=1,\ldots,n}\}$. The customer-perceived value of customization thus becomes a joint utility of individual utilities for every customizable feature, i.e.

$$U(\Delta F) = \sum_{i=1}^{n} (w_i U_i(\Delta F_i)), \tag{15}$$

where w_i indicates the relative importance (customer preference) of each requirement.

Conjoint analysis is an effective approach used to measure customer preference and assess utility functions for multiple product attributes [50]. Considering that a large number of attributes may be involved, this research applies adaptive conjoint analysis [51] to explore customer utilities by asking customers to rate a group of testing profiles in an interactive setting. Response surfaces can be created to simulate testing profiles. Other approaches, such as Kano Diagrams [52] and the Analytic Hierarchy Process [53] can also be applied to refine utility values.

6. Customizability analysis

Corresponding to multiple customizable features, the analysis of design customizability involves a set of indices, one for each individual feature (customization requirement), that is, $\mathrm{CI}^{\mathrm{D}} \sim \{\mathrm{CI}_i^{\mathrm{D}}|_{i=1,\ldots,n}\}$. The cost effectiveness of customization in production, however, can always be measured in terms of cycle time performance, regardless of that various types of process variations may result from design changes.

There are basically two types of customizability analysis problems. Type I is associated with design evaluation, more specifically, alternative selection. Its task is to select the most appropriate alternative from a finite set of product customization concepts. For this purpose, the utility measure and the design and process customizability indices are of primary importance among many evaluation criteria. This type of customizability analysis exhibits the classic multicriteria alternative evaluation problem as reviewed by Jiao and Tseng [54].

Type II is regarding design optimization—determining optimal settings of design parameters for a given customization alternative (its utility is given and does not change during the optimization of design parameters) while maximizing the overall cost effectiveness of customization. As shown in Table 1, the optimization becomes how to bring the customizability indices as close to 1 as possible. In the formulation of goal programming, the indices are treated as goals and the objective is to minimize the overall deviations of the indices from 1. Goal programming has been a commonly used technique in decision-based design [55].

Table 1
Design optimization for customizability

Given
A customization alternative to be improved, consisting of:
Customization requirements:
$F_{\mathrm{dr}_i}, w_{\mathrm{dr}_i}, F_{\mathrm{dr}_i}^{\mathrm{L}}, F_{\mathrm{dr}_i}^{U}, U_i(F_{\mathrm{dr}_i}),\ i = 1, \ldots, n;$
Product platform system models:
$F_{\mathrm{sr}_i}(\bar{D}), F_{\mathrm{sr}_i}^{\mathrm{L}}(\bar{D}), F_{\mathrm{sr}_i}^{\mathrm{U}}(\bar{D}), p_i(F_{\mathrm{sr}_i}(\bar{D}));$
Process platform system models:
$\mathrm{USL}_{\mathrm{T}}, \mu_{\mathrm{T}}(\bar{D}), \sigma_{\mathrm{T}}(\bar{D});$

Find
Design parameters:
$\bar{D} = \{D_j|_{j=1,\ldots,m}\};$

Satisfy
System constraints:
$F_{\mathrm{sr}_i}^{\mathrm{L}}(\bar{D}) \le F_{\mathrm{sr}_i}(\bar{D}) \le F_{\mathrm{sr}_i}^{\mathrm{U}}(\bar{D}), w^{\mathrm{D}} + w^{\mathrm{P}} = 1;$
System goals:
$\mathrm{CI}_i^{\mathrm{D}} + \Delta_i^{\mathrm{D}} = 1, \mathrm{CI}^{\mathrm{P}} + \Delta^{\mathrm{P}} = 1;$
Bounds:
$0 \le \Delta_i^{\mathrm{D}} \le 1, 0 \le \Delta^{\mathrm{P}} \le 1;$

Objective
Minimize preemptive deviation function (lexicographic minimum):
$$Z = w^{\mathrm{D}} \sum_{i=1}^{n} (w_{\mathrm{dr}_i} \Delta_i^{\mathrm{D}}) + w^{\mathrm{P}} \Delta^{\mathrm{P}}.$$

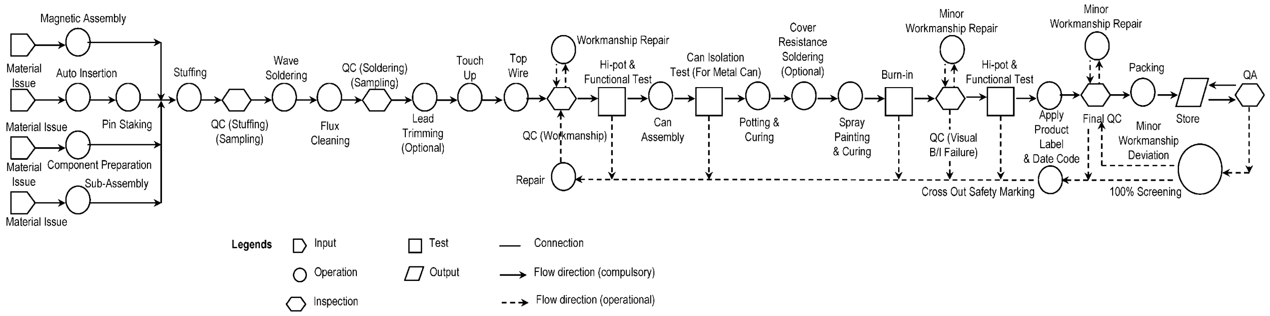

Fig. 6. The process platform for encapsulated AC/DC converters.

STANDARD TIME CALCULATION SHEET FOR AC/DC MODELS LAST UPDATED: JAN-03-95
============ ==================================== BY ROGER JIAO
PART NO.: 724830-251 MODEL NO.: ALP45-7608 DATE : 10-Jul-97
STD TIME : 0.5143 HOUR

NOTE : [M= FREQUENCY OF HANDLING THE PCB UNLESS SPECIFIED OTHERWISE]
[N= NO. OF COMPONENTS UNLESS SPECIFIED OTHERWISE]

CODE	DESCRIPTION	M	N	CYCLE TIME (SECOND)	TOTAL (SEC)	
WORKCENTRE : PCB PREPARATION						
ST15	SOLDER MASK WITH TAPE [N= NO. OF POINTS]	M =	N =	3.24 M + 10.08 N	0.0	
ST15	ADHERE TAPE ON PCB [N= NO. OF TAPES]	M =	N =	3.24 M + 5.04 N	0.0	
CP21	MOUNT H/S BY POP RIVETS [N= NO. OF RIVETS]		N =	11.99 N	0.0	
CP23	SILK SCREEN PAINTING	M =		83.99 M	0.0	0
WORKCENTRE : AUTO-INSERTION						
AI01	AUTO-INSERT AXIAL COMPONENTS	M = 1	N = 19	24.01 M + 0.94 N	41.9	
	[M = NO. OF PCB, N = NO. OF COMPONENTS]					
WORKCENTRE : COMPONENT PREPARATION & STUFFING						
CP02	2-LEAD AXIAL COMPONENT H-M WITH BEND & CUT		N = 1	11.88 N	11.9	
CP02	2-LEAD AXIAL COMPONENT V-M WITH BEND & CUT		N = 6	12.60 N	75.6	
CP02	2-LEAD RADIAL COMPONENT V-M WITH BEND & CUT		N = 14	12.96 N	181.4	
CP02	BRIDGE DIODE V-M		N =	11.16 N	0.0	
ST08	FUSE & FUSE GRIP		N = 1	21.24 N	21.2	
CP02	JUMPER WIRE WITH BENT LEAD (BARE WIRE)		N = 1	23.40 N	23.4	
FA05	TOP WIRE (STRIP + CRIMP + STUFF)	M =	N =	M + 0.00 N		
ST09	[M= NO. OF WIRES , N= TOTAL NO. OF CRIMPED ENDS]					
ST11	INDUCTOR WITH BENT & CUT LEAD		N = 3	21.60 N	64.8	
CP12	CONNECTOR WITH STRAIGHT PIN REMOVED & LEAD TRIMMEI		N = 2	13.32 N	26.6	
ST14	TRANSFORMER WITH N LEAD BENT	M = 2	N = 8	12.60 M + 1.44 N	36.7	
	[M= NO. OF XFMR , N= TOTAL NO. OF BENT LEADS]					
ST14	INSERT H/S ASSY ONTO PCB	M = 2	N = 3	9.00 M + 5.40 N	34.2	
	[M= NO. OF H/S , N= NO. OF TRANSISTOR]					
ST17	INSERT DAUGHTER BOARD		N = 1	5.04 N	5.0	481
WORKCENTRE : PACKING (L: ROW, M: COLUMN, N: LAYER, Z: NO. OF PCB IN /						
PA04	FBG, (PBG)	L = 2				
	PE FOAM -> BAG -> SHIPPING CARTON	M = 5		(61.6+4LMN+16.9N)/LMN	11.8	
		N = 1				
PA06	LABEL [N= NO. OF LABELS]		N = 2	13.32 N	26.6	
PA07	DATE CODE		N =	2.52 N	0.0	
	LABEL SHIPPING CARTON		N = 1	19.08 N	19.1	58
WORKCENTRE : MISCELLENOUS						
MC12	SOLDER FOIL TO H/S [N= NO. OF FOILS]		N =	20.16 N	0.0	
MC13	APPLY THERMAL GREASE [N= NO. OF POINTS]	M =	N =	8.28 M + 4.68 N	0.0	
MC14	ADHERE WIRE BY TAPE BEFORE LOADING ON CARRIER		N =	28.08 N	0.0	
MC17	PRINT TEST DATA		N =	60 N	0.0	0
				SUB-TOTAL:	1349.7	SECON
WORKCENTRE : SUB-STORE						
SS01	SUB-STORE MISCELLANEOUS OPERATION					
	POWER: <150W	M = 1		0.019 T (5/260)	25.9	
	POWER: >150W	M =		0.036 T (4/112)	0.0	
WORKCENTRE : REPAIR (ONLY FOR OPERATOR)						
RP01	REPAIR (POWER: <50W)	M = 1		0.023 T	31.2	
	REPAIR (POWER: 50W-200W)	M =		0.039 T	0.0	
WORKCENTRE : RE-TESTING						
RT01	LOW-POWER(1-150W)	M = 1				
RT01	1ST TEST			0.016 (DEFECT RATE)	2.2	
RT01	BURN IN			0.003 (DEFECT RATE)	0.5	
RT01	2ND TEST			0.006 (DEFECT RATE)	2.3	
	ADDITIONAL TEST TIME				0.0	
				SUB-TOTAL:	1411.7	SEC
					0.3921	HOUR
				TECHNICAL ALLOW : + 22%	0.0863	HOUR
					0.4784	HOUR
				MANAGEMENT ALLOW : + 7.5%	0.0359	HOUR
				TOTAL STANDARD TIME:	**0.5143**	**HOUR**

** This sheet has been truncated due to space limitation.*

Fig. 7. Spreadsheet for standard time calculation.

Table 2
Specifications of platforms and the customization

	Specification	BPI	BPII
Product platform	F_1 (%)/$u(F_1)$	[80, 88]/Triangular	[76, 80]/Triangular
	F_2 (kh)/$u(F_2)$	[600, 800]/Triangular	[260, 700]/Triangular
	F_3 (ppmv)/$u(F_3)$	[60, 100]/Triangular	[70, 110]/Triangular
	F_4 (W/in.^{3})/$u(F_4)$	[30, 50]/Triangular	[20, 45]/Triangular
	F_5/$u(F_5)$	Good/Triangular	Medium good/Triangular
	D_1(W)/$p(D_1)$	[40, 120]/Normal	[30, 100]/Normal
	D_2 (#)/$p(D_2)$	{2, 3, 4}/Normal	{2, 3, 4}/Normal
Process platform	μ (min)	48.7	32.6
	σ (min)	7.8	4.7
	USL_{LT} (min)	76.4	56.5
Customization requirements	F_1 (%)/$u(F_1)$	80 ± 4/Triangular	
	F_2 (kh)/$u(F_2)$	700 ± 100/Triangular	
	F_3 (ppmv)/$u(F_3)$	70 ± 5/Triangular	
	F_4 (W/in.^{3})/$u(F_4)$	30 ± 5/Triangular	
	F_5/$u(F_5)$	Medium/Triangular	

In general, a customized design based on existing product platforms involves both types I and II problems. To meet specific customer needs, for instance, we have to determine the most appropriate candidate (e.g. a base product), with which customization can begin. This is a type I problem. After locate a candidate, we have to decide the most cost-effective customization by determining optimal settings of relevant design parameters. This becomes a type II problem. Finally, this new design is justified and in turn may be added to the product platform for future use.

7. Application case

A simplified case study in a power supply company is presented here. Usually specification of the power supply unit cannot be determined in substantial detail until the host system design becomes elaborate enough. As a result, a custom power supply fitting to the host system is always the practice. To implement mass customization, the first task is to construct product and process platforms. A product platform (e.g. encapsulated AC/DC converters) consists of five customizable features, including efficiency (F_1), reliability/MTBF (F_2), noise (F_3), size (F_4), and compatibility (F_5), along with two design parameters: power rate (D_1) and number of outlets (D_2). As regards the construction of product platforms, Jiao and Tseng [56] provide the details of a methodology.

The process platform is constructed based on standard routings (i.e. the GBOO), as shown in Fig. 6. A popular technique for work measurement, Maynard Operation Sequence Technique (MOST®) [57], is adopted as the core for the process platform to compile standard-time data associated with the standard routings. All standard time estimates obtained from the MOST® are validated according to the actual data of existing products and processes. Then the TERs for individual operations are induced in connection to the key design features and variety parameters associated with the specific product platform. The derivation of TERs is based on the regression analysis that provides the formula for calculating the time for various elements contained in the study. Fig. 7 shows an example of standard-time calculation sheet.

To meet a custom order, an appropriate product platform should be identified for customization. As shown in Table 2, two platform alternatives (BPI and BPII) can be used to accommodate the customization requirements that are described as a set of customer needs. These two platforms are developed based on different product technologies (i.e. different topologies of power conversion). Selection of the candidate for customization is deemed to be the type I customizability analysis problem—to select the best alternative. While the achieved performances of D_1 and D_2 are assumed to be normally distributed, the preference functions are defined in triangular forms as depicted in Fig. 8. This definition is

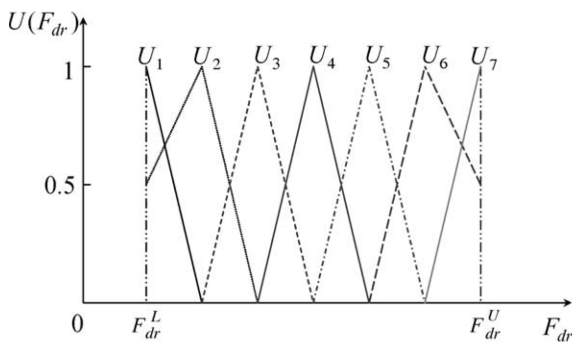

Fig. 8. Triangular preference functions.

Table 3
Results of customizability analysis

Analysis	BPI	BPII	BPI*
CI_1^D	0.373	0.392	0.444
CI_2^D	0.217	0.156	0.263
CI_3^D	0.549	0.556	0.590
CI_4^D	0.196	0.681	0.365
CI_5^D	0.707	0.365	0.556
CI^P	0.163	0.801	0.222
U	0.89	0.67	0.89
$D_1 = 76$;			$D_2 = 3$

also adopted for the membership functions of the universe of discourse for fuzzy variable, F_5.

The implementation of determining customer-perceived utility using conjoint analysis is provided by Du et al. [49]. Table 3 shows the results of all customizability indices and utility estimates that are calculated using Eqs. (4), (12) and (15). In the analysis, the discrete (D_2) and fuzzy (F_5) variables can be handled in the similar way to that of continuous variables. Following a fuzzy ranking approach [54], platform BPI is selected as the base product for the customization owing to its superior customizability to its counterpart (BPII).

Next, a customized design (BPI*) should be derived from BPI. This is the type II problem—design optimization. To deliver the expected utility (0.89), the optimal settings of design parameters ($D_1 = 76$; $D_2 = 3$) are determined following the goal programming model in Table 1. To perform goal programming, we use CPLEX 7.0 optimizer provided by ILOG (http://www.ilog.com/products/cplex/). As shown by the values of customizability indices in Table 3, design BPI* achieves an overall better customizability than its origin (BPI). Fig. 9 shows the response surface of utility for all possible customized designs derived from platform BPI with regards to diverse settings of design parameters (D_1 and D_2).

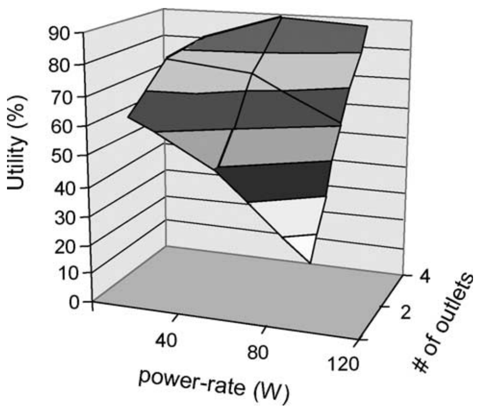

Fig. 9. The utility response surface of platform BPI.

Table 4
Comparison of optimization results

Solution strategy	Design parameters		Performance	
	D_1 (W)	D_2 (#)	Utility (U)	Cost ($)
BPI* (optimizing customizability)	76	3	0.89	50.3
BPI^U (maximizing utility)	66	4	0.90	84.9
BPI^C (minimizing cost)	89	2	0.12	42.8

Table 4 gives a comparison of different optimization strategies. The performance of different solutions is compared according to the achievement of utility and the estimated cost. Product costing is based on the methodology reported by Jiao and Tseng [47]. Solution BPI^U results from the maximization of utility, whilst solution BPI^C aims at minimizing the cost. Solution BPI^U produces the maximal utility (0.90) at the price of being most costly (84.9). On the contrary, solution BPI^C yields the minimal cost (42.8) while sacrificing the utility (the poorest among the three). By optimizing customizability, however, solution BPI* reaches an overall optimum in terms of both utility (0.89) and cost (50.3).

8. Conclusions

Customizability analysis necessitates the justification of cost effectiveness of customization around three pillars: the customer-perceived value, necessary design changes, and related process variations. Conjoint analysis helps explore customer-perceived value of multiple customizable product features independent of diverse design solutions. The application of information content measure to design customizability analysis excels in connecting customer satisfaction to the technical capability of a design. As a dimensionless scalar quantity, the design customizability index treats all variables alike, regardless of their physical origins. Such a measure provides a perfect common metric for assessing various technical criteria that are inherently incomparable due to their heterogeneous metrics.

Modeling the economic latitude of customization as cycle time performance can alleviate the difficulties in traditional cost estimation which is tedious and less accurate. Adopting the rationale of process capability analysis, the process customizability index summarizes the characteristics of production into one indicator and enables a proxy for the cost of customization to be assessed in terms of cycle times, thus providing a basic input for decisions regarding operations.

In the formulation of the indices, the probabilistic design aspect of customization is taken into account, in that the utility, information content and process capability are all based on probabilistic formulations. This facilitates the handling of uncertainties involved in customer needs, design changes and process variations related to customization. By introducing these indices, customization can be addressed as either a traditional design evaluation or optimization problem.

Acknowledgements

The authors would like to express their sincere thanks to Professor Num P. Suh for his valuable advice. Gratitude is also extended to the anonymous referees and the Editor for their constructive comments.

References

[1] Pine BJ. Mass customization: the new frontier in business competition. Boston: Harvard Business School Press; 1993.
[2] Tseng MM, Jiao J. Design for mass customization. Ann CIRP 1996; 45(1):153–6.
[3] Meyer M, Lehnerd AP. The power of product platform: building value and cost leadership. New York: Free Press; 1997.
[4] Sanderson SW, Uzumeri M. Managing product families. Management and organization series, Singapore: McGraw-Hill; 1997.
[5] Da Silveira G, Borenstein D, Fogliatto FS. Mass customization: literature review and research directions. Int J Prod Econ 2001;72(1): 1–13.
[6] Simpson TW. Product platform design and customization: status and promise. Special issue on platform product development for mass customization. AIEDAM 2004;18(2).
[7] Jiao J, Tseng MM, Ma Q, Zou Y. Generic bill of materials and operations for high-variety production management. Concurr Engng: Res Appl 2000;8(4):297–322.
[8] Martin MV, Ishii K. Design for variety: a methodology for understanding the costs of product proliferation. ASME Design Theory and Methodology Conferences. Paper No. DTM-1610, Irvine, CA; 1996.
[9] Martin MV, Ishii K. Design for variety: development of complexity indices and design charts. ASME Advances in Design Automation Conferences. Paper No. DFM-4359, Sacramento, CA; 1997.
[10] Gonzalez-Zugasti JP, Otto KN, Baker JD. Assessing value for platformed product family design. Res Engng Des 2001;13(1): 30–41.
[11] Simpson TW, Maier JRA, Mistree F. Product platform design: method and application. Res Engng Des 2001;13(1):2–22.
[12] Conner C, de Kroon JP, Mistree F. A product variety tradeoff evaluation method for a family of cordless drill transmissions. ASME Design Engineering Technical Conferences. Paper No. DAC-8625, Las Vegas, NV; 1999.
[13] Simpson TW. A concept exploration method for product family design. PhD Dissertation. Georgia Institute of Technology, Atlanta, GA; 1998.
[14] Blackenfelt M. Profit maximization while considering uncertainty by balancing commonality and variety using robust design. ASME Design Engineering Technical Conferences. Paper No. DFM-14013, Baltimore, MD; 2000.
[15] Collier DA. The measurement and operating benefits of component part commonality. Decis Sci 1981;12(1):85–96.
[16] Siddique Z. Common platform development: designing for product variety. PhD Dissertation. Georgia Institute of Technology, Atlanta, GA; 2000.
[17] Jiao J, Tseng MM. Understanding product family for mass customization by developing commonality indices. J Engng Des 2000;11(3):225–43.
[18] Wacker JG, Trelevan M. Component part standardization: an analysis of commonality sources and indices. J Oper Mgmt 1986; 6(2):219–44.
[19] Kota S, Sethuraman K, Miller R. A metric for evaluating design commonality in product families. ASME J Mech Des 2000;122(4): 403–10.
[20] McAdams DA, Stone RB, Wood KL. Functional independence and product similarity based on customer needs. Res Engng Des 1999; 11(1):1–19.
[21] McAdams DA, Wood KL. A quantitative similarity metric for design-by-analogy. ASME J Mech Des 2002;124(2):173–82.
[22] Jiao J, Tseng MM. Fundamentals of product family architecture. Integr Manufact Syst 2000;11(7):69–483.
[23] Martin MV, Ishii K. Design for variety: developing standardized and modularized product platform architectures. Res Engng Des 2002; 13(4):213–35.
[24] Ulrich K. The role of product architecture in the manufacturing firm. Res Policy 1995;24(3):419–40.
[25] Ho T-H, Tang CS. Product variety management: research advances. Boston, MA: Kluwer; 1998.
[26] Kekre S, Srinivasan K. Broader product line: a necessity to achieve success. Mgmt Sci 1990;36(10):1216–31.
[27] Banker RD, Datar SM, Kekre S. Relevant costs, congestion and stochasticity in production environments. J Acc Econ 1988;10(3): 171–97.
[28] MacDuffy JP, Sethuraman K, Fisher ML. Product variety and manufacturing performance: evidence from the international automotive assembly plant study. Mgmt Sci 1996;42(3):350–69.
[29] Herrmann JW, Chincholkar MM. Design for production: a tool for reducing manufacturing cycle time. ASME Design Engineering Technical Conferences. Paper No. DFM-14002, Las Vegas, NV; 2000.
[30] Kusiak A, He DW. Design for agility: a scheduling perspective. Robotics Comput Integr Manufact 1998;14(4):415–27.
[31] Tseng MM, Jiao J. Mass customization. In: Salvendy G, editor. Handbook of industrial engineering, 3rd ed. New York: Wiley; 2001. p. 684–709. [chapter 25].
[32] Jiao J, Huang GQ, Tseng MM. Special issue on concurrent enterprising for mass customization. Concurr Engng: Res Appl 2003;12(1). in print.
[33] Suh NP. Axiomatic design: advances and applications. New York: Oxford University Press; 2001.
[34] Du X, Jiao J, Tseng MM. Architecture of product family: fundamentals and methodology. Concurr Engng: Res Appl 2001; 9(4):309–25.
[35] Chen W, Allen JK, Mistree F. The robust concept exploration method for enhancing concurrent systems design. Concurr Engng: Res Appl 1997;5(3):203–17.
[36] Thurston DL. A formal method for subjective design evaluation with multiple attributes. Res Engng Des 1991;3(2):105–22.
[37] Chen W, Yuan C. A probabilistic design model for achieving flexibility in design. ASME J Mech Des 1999;121(1):77–83.
[38] Chen W, Simpson TW, Allen JK, Mistree F. Satisfying ranged sets of design requirements: a design metric using design capability indices. Engng Optim 1999;31(4):615–39.
[39] Simpson TW, Rosen D, Allen JK, Mistree F. Metrics for assessing design freedom and information certainty in the early stages of design. ASME J Mech Des 1998;120(4):628–35.
[40] Siddall JN. Probabilistic engineering design: principles and applications. New York: Marcel Dekker; 1983.
[41] Wortmannm JC, Muntslag DR, Timmermans PJM. Customer-driven manufacturing. London: Chapman & Hall; 1997.
[42] Hegge HMH, Wortmann JC. Generic bill-of-material: a new product model. Int J Prod Econ 1991;23(1–3):117–28.

[43] Hegge HMH. A generic bill-of-material processor using indirect identification of products. Prod Plan Control 1992;3(3): 336–42.
[44] Tielemans PFJ. Lead time performance in manufacturing systems. PhD Thesis. Rotterdam School of Management, Eburon, Delft; 1995.
[45] Zijm WHM, Buitenhek R. Capacity planning and lead time management. Int J Prod Econ 1996;46–47:165–79.
[46] Hodson WK. Maynard's industrial engineering handbook. New York: McGraw-Hill; 1992.
[47] Jiao J, Tseng MM. A pragmatic approach to product costing based on standard time estimation. Int J Oper Prod Mgmt 1999;19(7): 738–55.
[48] Kane VE. Process capability indices. J Qual Technol 1986;18(1): 41–52.
[49] Du X, Jiao J, Tseng MM. Analyzing customer value in product customization; 2003, in review.
[50] Green PE, DeSarbo WS. Additive decomposition of perceptions data via conjoint analysis. J Consumer Res 1978;5(1):58–65.
[51] Sawtooth Software. http://www.sawtooth.com/; 2002.
[52] Kano N, Seraku N, Takahashi F, Tsuji S. Attractive and must-be quality. J Jpn Soc Qual Control 1984;14(2):39–48.
[53] Saaty TL. The analytic hierarchy process. New York: McGraw-Hill; 1980.
[54] Jiao J, Tseng MM. Fuzzy ranking for concept evaluation in configuration design for mass customization. Concurr Engng: Res Appl 1998;6(3):189–206.
[55] Mistree F, Smith WF, Bras BA, Allen JK, Muster D. Decision-based design: a contemporary paradigm for ship design. Trans Soc Naval Architects Marine Engrs 1990;98:565–97.
[56] Jiao J, Tseng MM. A methodology of developing product family architecture for mass customization. J Intell Manufact 1999;10(1): 3–20.
[57] Maynard, MOST® for Windows™. http://www.hbmaynard.com/; 1997.

Dr Jianxin Jiao is Assistant Professor of Systems and Engineering Management, School of Mechanical and Production Engineering, Nanyang Technological University in Singapore. He is convener and coordinator of Global Manufacturing and Logistics Forum at Nanyang. He received a PhD from Department of Industrial Engineering and Engineering Management, Hong Kong University of Science and Technology. He holds a Bachelor degree in Mechanical Engineering from Tianjin Institute of Light Industry in China, and a Master degree in Mechanical Engineering from Tianjin University in China. He has worked as a lecturer in Department of Management at Tianjin University. His research interests include mass customization, design theory and methodology, reconfigurable manufacturing systems, engineering logistics, and intelligent systems.

Professor Mitchell M. Tseng is Professor of Industrial Engineering and Director of Advanced Manufacturing Institute at Hong Kong University of Science and Technology. He holds a BS degree in Nuclear Engineering from the National Tsing Hua University in Taiwan, a MSc degree and a PhD in Industrial Engineering from Purdue University. He joined the Hong Kong University of Science and Technology as the founding department head of Industrial Engineering in 1993 after holding executive positions at Xerox and Digital Equipment Corporation for almost two decades. He previously held faculty positions at University of Illinois at Champaign Urbana and Massachusetts Institute of Technology. His research interests include global manufacturing systems, mass customization, information systems applications, and business process design.